Research on Intelligent Agricultural Monitoring and Control System Based on Neural Networks in the Internet of Things Environment

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Abstract: *In today's rapidly advancing information technology landscape, the Internet of Things (IoT) has profoundly impacted traditional agriculture. IoT technology, as an intelligent solution, enables real-time data collection, processing, and analysis, significantly enhancing the efficiency and intelligence of agricultural production. Among these advancements, the neural network-based intelligent agricultural monitoring system stands out. This system not only monitors the agricultural production environment in real-time but also employs deep learning algorithms to predict future trends, guiding agricultural practices to achieve precision farming. Therefore, exploring the intelligent agricultural monitoring and control system based on neural networks in the IoT environment holds significant importance.*

Keywords: *Internet of Things; Neural Networks; Intelligent Agriculture; Monitoring and Control*

Introduction

With the global population increasing, issues of food security and sustainable agricultural development have become increasingly prominent. Traditional agricultural production methods are increasingly inadequate to meet the demands of modern agriculture. Intelligent agriculture, represented by neural networks, offers new solutions to these challenges. This system can analyze and learn from vast amounts of agricultural data, real-time monitoring of soil moisture, temperature, light intensity, and other agricultural production factors, thereby improving crop yield and quality, reducing resource waste, and promoting sustainable agricultural development. Consequently, exploring how to apply neural networks in intelligent agricultural monitoring and control systems is one of the current hot topics in the agricultural field.

1. Overview of Neural Networks

1.1 Basic Structure of Neural Networks

A neural network is a computational model that mimics the working principles of the human brain, playing a crucial role in the field of artificial intelligence. This network consists of multiple layers, primarily including an input layer, one or more hidden layers, and an output layer. Each layer comprises multiple nodes (or neurons) that are interconnected through weighted connections. The input layer serves as the entry point for external information, converting data such as images, text, or audio into a format that the network can process.

The hidden layers are located between the input and output layers and are the core of the neural network, potentially containing one or more hidden layers. Each node in these layers is connected to every node in the previous layer by weights. While the nodes in the input layer do not perform any calculations, they play a vital role in information transmission.

As data flows from the input layer to the hidden layers, each connection applies a weight to the signal. The weighted signals are accumulated within the nodes and processed through an activation function. The activation function is an essential component of the neural network, introducing non-linear factors that enable the network to address complex, non-linearly separable problems. Common activation functions include Sigmoid, ReLU (Rectified Linear Unit), and Tanh, which determine whether and how signals are transmitted to the next layer.

The output layer is the final layer of the neural network, responsible for generating the final output results. The design of the output layer depends on specific task requirements. For example, in classification tasks, the number of nodes in the output layer typically corresponds to the number of classes, with each node representing the probability of a particular class; in regression tasks, a single node may be sufficient to output a predicted value.

During training, the neural network learns to extract useful information from input data by continuously adjusting the weights of the connections between layers to minimize prediction errors and improve model performance. This learning capability enables neural networks to exhibit strong performance across various applications, from image recognition to natural language processing and complex decision support systems.[1]

1.2 Common Types of Neural Networks

Feedforward Neural Networks (FNNs) are considered the simplest neural network structure, where information flows only in one direction—from the input layer to the output layer—potentially passing through one or more hidden layers. A defining characteristic of feedforward neural networks is the absence of loops, meaning that the current output solely depends on the current input.

Convolutional Neural Networks (CNNs) are widely used in processing data with a grid-like structure, such as images. By combining convolutional layers, pooling layers, and fully connected layers, CNNs automatically and efficiently capture the spatial hierarchies of images, recognizing local features like edges and textures. The pooling layers reduce the dimensionality of network parameters, decrease computational load, and enhance the network's robustness. CNNs have achieved significant success in image recognition, video analysis, and natural language processing.

Recurrent Neural Networks (RNNs) are particularly well-suited for processing sequential data. Unlike feedforward neural networks, RNNs introduce loops, allowing the current output to depend on the previous computation results. This structure enables RNNs to retain memory and apply it to current outputs, making them particularly effective for time-series data processing. RNNs have been successfully applied in language modeling, text generation, and speech recognition.[2]

2. Application Advantages of Neural Network-Based Smart Agricultural Monitoring and Control Systems

2.1 Precision Irrigation Control

Traditional agricultural irrigation methods primarily rely on farmers' experience, which not only wastes substantial water but also makes it difficult to achieve optimal irrigation results. A neural network-based smart agricultural monitoring system can simulate the processing mechanisms of the human brain, automatically adjusting and optimizing decision models based on extensive data analysis. This system first employs sensors to monitor parameters such as soil moisture and weather conditions in real time, inputting this data into the neural network model. Based on the current soil moisture, predicted weather changes, and crop growth needs, the system can accurately calculate the optimal irrigation timing and water quantity. This precise control not only prevents water resource wastage but also ensures sufficient moisture supply throughout the entire growth period, significantly enhancing yield and quality.

2.2 Pest and Disease Prevention and Control

Pests and diseases pose serious threats to agricultural production. Traditional control measures often rely on chemical pesticides, increasing production costs and potentially harming the environment and human health. The agricultural smart monitoring system established using neural network technology can provide early warnings about pest occurrences, offering scientific control recommendations to farmers. By analyzing historical pest data alongside current environmental information, the system employs neural network pattern recognition to accurately predict the timing and severity of pest outbreaks. Additionally, the system can automatically adjust irrigation and fertilization strategies based on these predictions, aiming to minimize or eliminate pesticide use.[3]

2.3 Crop Growth Monitoring

In terms of monitoring crop growth, a neural network-based smart agricultural monitoring system can accurately and in real-time gather information on crop conditions, such as plant height, leaf area, and health status. This capability is made possible through high-precision sensors and advanced image recognition technologies. By processing and analyzing this data using neural networks, the system can provide farmers with comprehensive information on crop growth. Moreover, the system can identify potential issues, such as pests or diseases, allowing farmers to take timely management actions to avoid or mitigate losses. The strong learning ability and adaptability of neural networks enable them to identify key factors affecting crop growth from vast agricultural datasets, predicting future trends. These predictions can provide farmers with scientific evidence to make more informed decisions regarding fertilization and irrigation, thereby enhancing crop growth rates and yields.

2.4 Climate Adaptation Recommendations

In terms of climate adaptation, the neural network-based smart agricultural monitoring system has also shown significant effectiveness. This system integrates and analyzes meteorological data to provide scientific guidance for farmers regarding planting times and crop selection. For example, if a drought is predicted in the near future, the system may recommend planting drought-resistant crops or adjusting planting plans to minimize losses. Based on big data analysis and predictions, the system enhances the flexibility and adaptability of agricultural production to address climate change challenges. Furthermore, the self-learning capability of neural networks allows the system to continuously optimize its climate adaptation strategies based on multi-source observational data, providing farmers with more precise decision-making support and driving ongoing optimization and innovation in agricultural production models.

3. Research on Smart Agricultural Monitoring and Control Systems Based on Neural Networks in IoT Environments

3.1 Environmental Monitoring and Data Collection

In an IoT environment, efficient and accurate environmental monitoring and data collection are crucial for neural network-based smart agricultural monitoring systems. This involves selecting appropriate sensors, such as temperature and humidity sensors, soil moisture sensors, and light intensity sensors, along with additional sensors for specific crops that may require monitoring of carbon dioxide concentration and nutrient elements. The scientific deployment of sensors is equally important to ensure comprehensive coverage of the farmland and minimize interference among sensors. IoT technology supports real-time transmission of sensor data to a central processing center through wireless networks such as Low Power Wide Area Networks (LPWAN), Bluetooth, and Wi-Fi. Choosing the right communication protocols and network architecture, while addressing signal interference in the farmland environment, is vital for ensuring the timeliness and accuracy of data transmission. Given the complexity of the farmland environment, the collected data may contain substantial noise; therefore, data preprocessing becomes a key step in improving data quality. This includes noise removal and normalization. Additionally, integrating data from multiple sensors can provide more comprehensive and precise environmental information, thereby optimizing the performance and predictive accuracy of the neural network model.[4-6]

3.2 Establishment of Neural Network Models

In establishing the neural network models for the smart agricultural monitoring system, data preprocessing is a critical first step. This involves cleaning and normalizing raw data, which includes removing irrelevant data points and scaling the data to the same range to reduce biases between different magnitudes. For agricultural monitoring, it is essential to focus on key factors such as temperature, humidity, soil pH, and light intensity, analyzing their correlations with crop growth. Techniques like Principal Component Analysis (PCA) can be employed for feature extraction and dimensionality reduction to identify significant features valuable for predicting crop growth, thereby improving modeling efficiency. Selecting the appropriate network architecture—such as Feedforward Neural Networks, Convolutional Neural Networks (CNNs), or Recurrent Neural Networks (RNNs)—is crucial for model performance. Moreover, determining the number of layers, neurons, and activation functions is essential for accurately simulating the impact of agricultural environments on crop growth. Utilizing deep learning for nonlinear fitting and employing backpropagation algorithms to continuously adjust model parameters will help reduce prediction errors. To prevent overfitting, cross-validation and regularization techniques are used. Independent validation datasets are employed to test model performance, assessing its predictive capability on unseen data. Model performance is comprehensively evaluated through metrics such as accuracy, recall, and F1 score, guiding adjustments to network structure and training algorithms to optimize learning rates. Furthermore, applying ensemble learning methods like model fusion and Boosting can enhance the predictive accuracy and stability of the model, ensuring the effectiveness and reliability of the smart agricultural monitoring system.

3.3 Intelligent Prediction and Decision-Making

The neural network-based smart agricultural monitoring system predicts crop growth trends, pest probabilities, and optimal harvest times by collecting parameters related to crop growth—such as temperature, humidity, nutrients, and light—while integrating historical data and applying deep learning algorithms. The system primarily utilizes CNNs for pest recognition, while RNNs and Long Short-Term Memory networks (LSTMs) are employed to process time-series data such as temperature and humidity, improving prediction accuracy. Intelligent predictions provide future trend data, aiding in the formulation of optimal decisions. The system integrates agricultural expert systems and machine learning technologies to analyze prediction results, automatically generating optimal agricultural management plans. For instance, if the prediction module forecasts a drought event in the near future, the decision module will determine the optimal irrigation strategy based on factors such as soil moisture, crop variety, and growth stage. When the likelihood of a pest outbreak is significant, the system can recommend specific biological control measures or chemical agents, along with the best timing and dosage for application. The system has built an efficient data processing and analysis platform, equipped with self-learning and optimization capabilities to meet the demands of processing vast and varied data types. As agricultural production conditions and technologies evolve, the system can flexibly incorporate new data sources and analytical modules, continuously learning to optimize decision models and improve the accuracy and efficiency of decisions.[7]

3.4 Automation Control

An automated irrigation system connects soil moisture sensors to a neural network controller, enabling real-time monitoring of soil moisture. The controller analyzes data to automatically determine whether to initiate irrigation, maintaining optimal moisture levels for crop growth while conserving water and enhancing yield. Smart fertilization equipment assesses soil nutrients and, based on neural network control, automatically adjusts fertilization plans according to the crop growth stage, ensuring that crops receive adequate nutrition to promote healthy growth. Lighting control devices in critical environments such as greenhouses automatically adjust lighting based on commands from the neural network controller, simulating natural light conditions to enhance photosynthesis and increase crop productivity.[8]

3.5 Intelligent Identification and Control of Pests and Diseases

Image recognition and deep learning technologies are key to achieving intelligent identification of pests and diseases. The system collects crop images in real-time through high-definition cameras in the field and analyzes these images using neural network algorithms, particularly convolutional neural networks (CNNs), to identify and classify pests and diseases. By training the neural network with labeled pest and disease images, the model learns to extract features from images, enabling precise classification. Over time and with data accumulation, the identification capability continually improves. Once the type of pest or disease is determined, the system automatically selects the most suitable control measures based on the type, severity, and environmental factors (such as weather and soil moisture). In the early stages of disease, biological control methods, such as releasing natural predators or spraying biological insecticides, are prioritized to reduce the use of chemical pesticides. For severe or difficult-to-control pests, specific chemical insecticides may be necessary. The system can also adjust the optimal timing and dosage of pesticide application based on weather forecasts and soil conditions, optimizing the effectiveness of pest and disease control.[9]

3.6 Harvest Prediction

Training a neural network model requires a substantial amount of historical data, including the growth periods of various crops throughout the year, climatic conditions they experienced, management practices, and the timing and quantity of the final harvest. By learning from these data, the neural network model can uncover complex relationships between different factors and the timing and quantity of harvests. For example, the model may learn that a particular crop grows faster under specific temperature and humidity conditions, allowing it to predict that the crop's maturity will occur earlier. Additionally, the model can identify relationships between parameters such as plant height, leaf color, and other growth indicators with expected yield, allowing it to forecast yield outcomes. During the prediction process, the neural network model receives real-time data feedback from IoT devices and adjusts its predictions accordingly. Over time, as the model accumulates more data—including both successful cases and anomalies—it further optimizes and corrects itself to enhance the accuracy and reliability of predictions. Based on this, it analyzes discrepancies between predicted and actual yields, providing scientific evidence for agricultural production.[10]

Conclusion

In summary, the neural network-based agricultural smart monitoring system achieves precise data collection and real-time monitoring analysis, effectively addressing challenges such as the difficulty in monitoring crop growth, low resource utilization, and the negative impact of environmental changes on crop growth in traditional agriculture. The application of neural network technology provides the system with powerful data processing and learning capabilities, enabling it to learn from historical data and predict future agricultural trends, thereby offering more scientific and precise decision-making support for agricultural production. Furthermore, by integrating advanced technologies such as IoT and artificial intelligence, a smart agricultural monitoring system based on these technologies can be established, providing technical support for efficient, intelligent, and sustainable agricultural development.

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